Measurement 91 (2016) 101–113

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

Extraction of microseismic waveforms characteristics prior to rock burst using Hilbert–Huang transform

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ARTICLE INFO

Article history:
Received 28 September 2015
Received in revised form 14 March 2016
Accepted 11 May 2016
Available online 13 May 2016

Keywords:
Rock burst
Microseism
Hilbert–Huang transform
Empirical mode decomposition
Precursor feature

ABSTRACT

This study provides a new research idea concerning rock burst prediction. The characteristics of microseismic (MS) waveforms prior to and during the rock burst were studied through the Hilbert–Huang transform (HHT). In order to demonstrate the advantage of the MS features extraction based on HHT, the conventional analysis method (Fourier transform) was also used to make a comparison. The results show that HHT is simple and reliable, and could extract in-depth information about the characteristics of MS waveforms. About 10 days prior to the rock burst, the main frequency of MS waveforms transforms from the high-frequency to low-frequency. What's more, the waveforms energy also presents accumulation characteristic. Based on our study results, it can be concluded that the MS signals analysis through HHT could provide valuable information about the coal or rock deformation and fracture.

1. Introduction

The documentation entitled "Energy Medium and Long-Term Development Plan Outline (2004–2020)" released by the State Council of China has made it very clear that China will adhere to the energy strategy that coal will continue to be the dominant energy for China in a long period. The stable, sustained and healthy development of coal resources is directly related to the national energy security. Chinese coal production and casualties account for approximately 37% and 70% of the world, respectively [1]. During mining, major catastrophic accidents occur frequently, such as coal and rock outburst, water burst, rock burst, roof accidents, and gas and coal dust explosion. In the latest decades, owing to the drying up of shallow resources, the mining depth and mining intensity gradually increases in China, which leads to the rapid increase of the frequency and intensity of these accidents. For instance, due to deep mining, rock bursts induce more destructive and sudden severe accidents, causing huge economic losses and casualties [2].

Previous studies on rock burst mainly focused on two aspects: (1) rock burst theoretical analysis based on the damage and failure mechanism; (2) rock burst monitoring and preventing. Numerous field investigations are being carried out in this respect, including rock mechanics and geophysical methods [3]. Microseismic (MS) monitoring is one of the various geophysical methods available. Since the 1940s, the United States Bureau of Mines has been applying MS to monitor the rock burst [4–6]. In recent years, the MS has gradually become a monitoring and early warning measure to ensure the safety of coal mines [7–16]. In the modern world, many countries seriously affected by rock burst have established the National Mine MS Monitoring Network, which provides real-time monitoring and early warning concerning rock burst, so as to reduce the damage caused by it. After a thorough review of statistical literature related to MS monitoring in coal mine, we found that most studies mainly focused on the hypocentral, the coal or rock rupture mechanism, and statistics features of MS events [17–20].

The MS monitoring system aims to capture the signals produced by rock or coal rupture [21]. Therefore, the methods to effectively identify the original MS waveforms are very important in order to analyze the activities that lead to the dynamic disasters. MS waveforms are typically time-varying and nonstationary signals, which contain abundant information about coal or rock rupture, therefore, it is necessary to extract the MS waveforms of coal or rock rupture. To extract all related information from these nonstationary MS signals, some time–frequency techniques have been listed in previous literatures. Fourier transform is the most traditional and classical time–frequency analysis method, which has been widely used in the signal analysis field [22–27]. However, Fourier transform is a

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http://dx.doi.org/10.1016/j.measurement.2016.05.045
0263-2241/

pure frequency domain analysis method with some limitations. For example, it can only provide information about the frequency characteristics of the whole signal in a given time, and it is strictly restricted by Heisenberg uncertainty principle. Moreover, the time resolution and frequency resolution cannot be arbitrarily small at the same time, that is to say, there is a contradiction in the time domain and frequency domain localization. Fourier transform also requires the signal is quasi-periodicity and stability [28,29]. Therefore, the Fourier transform is more suitable for analyzing the signals in the quasi-steady state. Wavelet analysis proposed by French geophysicists in the early 1980s might be useful for the extraction of in-depth information from the nonlinear signals [30]. To the low frequency part of the signal, through wide time window, it presents the time-domain resolution low and frequency resolution high. To the high frequency part of the signal, through narrow time window, it causes the time-domain resolution high and frequency resolution low. These characteristics make the wavelet has the features of "microscope" and "telescope." However, the wavelet transform is only an adjustable window Fourier spectral analysis, it is also restricted by the Heisenberg uncertainty principle. The characteristic of wavelet finite length will cause the leakage of signals energy, and the analysis results obtained from the same signal based on different wavelet basic function will present a significant difference [31]. Regardless of these shortcomings, as an important harmonic analysis method, the wavelet method is one of the best available techniques to analyze the nonlinear signals, which is common used in image processing, speech analysis, pattern recognition, quantum physics, and seismic waveform [32–37].

To overcome the aforementioned shortcomings, a novel method called the Hilbert–Huang Transform (HHT) was proposed. The HHT is a powerful tool for processing nonlinear and nonstationary signals, through which the time-varying fundamental frequency of the system can be estimated. The primary features of the HHT superior to other methods are that it can deal with the nonlinear signals objectively and provide an accurate time resolution for the signal energy-frequency representation [38]. The effectiveness of HHT in signal analysis has been demonstrated by its successful application to monitor and predict the earthquakes and blasts. Additionally, it is also used in various fields such as biomedicine, finance, and geology (e.g., estimating VLF for seismic ionospheric and geophysical signals) [39–45].

Even after a close examination of the rock burst previously published in the literatures, it remains difficult to accurately evaluate the MS waveform response of rock burst. In this paper, the signal characteristics of MS waveforms with the approach of rock burst were analyzed by the HHT method. It can be applied to monitoring and early warning of rock burst in colliery and revealing the formation of cracks with the approach of rock burst.

2. Fundamentals of the Hilbert–Huang Transform

The HHT, a time–frequency method developed by Huang et al. in the late 1990s [46,47], is suited for splitting a multicomponent nonstationary and monocomponent signals into a sum of elementary modes, which consists of two sections: empirical mode decomposition (EMD) and Hilbert spectrum analysis (HSA). In general, EMD is based on the empirical estimation to decompose a signal into a finite set of intrinsic mode functions (IMFs), which permits a well-behaved Hilbert transform. IMF is a simple harmonic function which satisfies the two conditions: (1) Over the entire time series, the number of extrema (either maxima or minima) and zero crossing point must be equal or differ at most by one; and (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The EMD algorithm has two purposes: (1) Remove the superposition of wave and (2) make the waveform more symmetrical. Any waveform can be decomposed as a function through a shifting process as follows:

(1) Find out all the extreme points of the original signal [$X(t)$].
(2) Use a cubic spline curve for all the extreme points, perform an interpolation by fitting the upper and lower envelopes of the original signal. Then, find the average of the upper and lower envelopes, which is indicated as a mean line [$m_1(t)$].
(3) Subtract the mean line [$m_1(t)$] from the original signal [$X(t)$].

$$h_1(t) = X(t) - m_1(t) \tag{1}$$

In general, only under ideal conditions $h_1(t)$ would be the first IMF component of the original signal. The decomposition of $h_1(t)$ may not necessarily satisfy the aforementioned two conditions. Therefore, the signal would be repeatedly decomposed.

(4) To obtain $h_{1k}(t)$, $h_1(t)$ as the original signal would be repeated k times, according to Steps 1–3. To analyze whether $h_{1k}(t)$ is one of the IMFs or not, it has to meet a final condition, which is calculated by the standard deviation (SD) of two consecutive signals $h_{1(k-1)}(t)$ and $h_{1k}(t)$.

The expression for SD is given as follows:

$$SD = \sum_{t=0}^{T} \left| \frac{|h_{1(k-1)}(t) - h_{1k}(t)|^2}{h^2_{1(k-1)}(t)} \right| \tag{2}$$

It has been shown that when SD is 0.2–0.3, the IMF of linearity and stability can be ensured, and IMF retains the corresponding physical significance [46,47]. When the SD meets the requirements, the decomposition process would be terminated, and $h_{1k}(t)$ becomes the first IMF component of the original $X(t)$, which represents the highest frequency component of $X(t)$

$$c1 = h_{1k}(t) \tag{3}$$

(5) Subtract the first IMF component ($c1$) from the original signal [$X(t)$] to obtain a residual signal [$r_1(t)$]

$$r_1(t) = X(t) - c1 \tag{4}$$

Here, $r_1(t)$ is regarded as a new original signal. By repeating Steps 1–4, we can obtain all the IMF components and a residual component (r), the presence of which indicates the original signal empirical mode (EMD) decomposition is completed.

Hilbert spectral analysis (HSA), an integration of all the IMF instantaneous frequencies and Hilbert amplitudes, is expressed as follows:

$$H(\varpi, t) = Re\sum_{i=1}^{n} ai(t)e^{i\varphi i(t)} \tag{5}$$

where Re denotes the real part of a complex data. If amplitude square is more desirable to represent energy density, then the squared values of amplitude can be substituted to produce the Hilbert energy spectrum.

If $H(\varpi, t)$ is integrated over time, the corresponding Hilbert marginal spectrum [$H(\varpi)$] is obtained

$$H(\varpi) = \int_0^T H(\varpi, t)d\varpi \tag{6}$$

Hilbert marginal spectrum [$H(\varpi)$] can truly reflect the presence possibility of the signal frequency in statistical analysis. Based on Hilbert marginal spectrum, the marginal Hilbert energy spectrum [ES (ϖ, t)] can be defined as follows:

$$ES(\varpi) = \int_0^T H^2(\varpi, t)d\varpi \tag{7}$$